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APPLICATIONS OF OPTIMAL BUILDING ENERGY SYSTEM SELECTION AND OPERATION

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ABSTRACT

Berkeley Lab has been developing the Distributed Energy Resources Customer Adoption Model (DER-CAM) for several years. Given load curves for energy services requirements in a building microgrid (µ·grid), fuel costs and other economic inputs, and a menu of available technologies, DER-CAM finds the optimum equipment fleet and operating schedule. This capability is being applied using a software as a service (SaaS) model. The evolution of this approach is demonstrated by description of four past and present projects: (1) a public access web site focused on solar photovoltaic generation and battery viability for large non-residential customers, (2) a building CO_2 emissions reduction operations problem for a university dining hall with potential investments considered, (3) a battery selection problem and a rolling operating schedule problem for a large County jail, and (4) the direct control of the solar-assisted heating ventilation and air conditioning system of a university building by providing optimised daily schedules that are automatically implemented in the building's energy management and control system. Together these examples show that optimisation of building μ·grid design and operation can be effectively achieved using SaaS.

Keywords: optimisation, mixed integer linear programming, microgrids, building systems scheduling, PV, solar thermal, batteries

INTRODUCTION

Background

Emerging technology offers the commercial building sector many promising applications for efficiency measures, solar photovoltaics (PV), solar thermal (ST) collection, and other renewable generation, combined heat and power (CHP), as well as demand response capability, and possibly grid ancillary service provision. Furthermore, on-site load management measures can reduce the costs of operating a facility, especially when complex tariffs or costly operating constraints apply.

To obtain best results, distributed resources, ancillary services, and passive efficiency measures should all be part of a systemic energy management strategy covering both equipment selection and operation. By contrast, current building design and operation approaches tend to consider each technology sequentially and largely in isolation. Since the viability of various technology alternatives are evaluated one-by-one, it is unlikely the outcome will come close to the site's global optimum. The most significant difference between results of non-optimising models such as RETScreen, and ones that find multiple solutions and rank them, such as HOMER **[1, 2],** and DER-CAM would be experienced when complex optimisation is beneficial, such as battery scheduling under a variable tariff.

The importance of the building sector in post-industrial economies is widely recognised, e.g. about 70% of total U.S. electricity use is consumed in buildings. Two key sources of potential electricity consumption growth, plug-in electric vehicle charging and ground source heat pump space heating, will likely further extend the sector's dominance. Choosing and operating multiple technologies on both supply and demand sides under complex tariff regimes, possibly involving feed-in rates and rewards for demand response and/or ancillary service provision, with highly variable building loads dependent on weather, occupancy, building repurposing, etc. forms a technical and economic problem that is unlikely to be solved by simple search algorithms and engineering rules of thumb.

This paper reports on efforts at the Lawrence Berkeley National Laboratory (LBNL or Berkeley Lab) to develop capabilities for attacking these challenges. Particularly, methods and software under ongoing development aim to aid optimum building equipment selection and operation under the conditions described above. Four examples of this work are described herein. 1. An operational open access optimisation tool, the Storage Viability and Optimization Web Service (SVOW) provides energy managers at large commercial and industrial facilities with preliminary investment decisions for PV and batteries **[3]**. 2. A direct data exchange link has been established between Berkeley Lab and a building on the University of California, Davis (UCD) campus. Suggested additional investments are provided, and based on monitored conditions and other data sources, week-ahead operating schedules are developed [4]. 3. Berkeley Lab assisted with making a large stationary battery selection for its local county jail, and will be finding ongoing optimal operating schedules for it as well as exploring demand response possibilities [5]. And 4., the solar-assisted heating ventilation and air conditioning (HVAC) system of a University of New Mexico (UNM) building is being controlled according to optimised daily schedules automatically implemented in the building's energy management and control system (EMCS).

Microgrids

While the methods described in this paper are applicable to various types of buildings under many administrative structures, a strong motivator for this research programme is the belief that our familiar centralised power system (*macrogrid*) is undergoing radical change that will fundamentally alter the nature of local electricity systems. This vision suggests that in addition to the highly centralised supply network and control paradigm with which we are so familiar, dispersed control will emerge at multiple levels of the power system and with multiple objectives.

One of these levels, namely control of a single buildings or a local grouping of buildings behind a single point of common coupling is often referred to as a *microgrid* or *μ·grid* **[6]**. A formal definition emerging from a *Conseil International des Grandes Réseaux Electriques* (CIGRÉ) working group on the topic asserts:

Microgrids are electricity distribution systems downstream of a utility substation containing loads and DER, (such as distributed generators, storage devices, or controllable loads) that can be operated in a controlled, coordinated way either while connected to the main power network or while islanded.

The notion that this new entity will be a feature of the future smart grid is achieving growing currency and offers appealing opportunities. This argument holds that appropriate incentive schemes together with the selection and operation of equipment, the purchase of fuels and endue devices, as well as the control of loads all under localised control, will result in more rational tradeoffs between alternatives. In other words, the market failures that have bedevilled building energy use historically, such as under-investment in efficiency measures and local resource harvesting, will be mitigated.

Outline

The Distributed Energy Resources Customer Adoption Model (DER-CAM) has been developed to solve the μ·grid equipment selection and operation problem analytically, and this paper reports on four applications **[7]**. The principles underlying DER-CAM are set out in the METHOD section, and the RESULTS section contains descriptions of the four projects together with results.

METHOD

Distributed Energy Resources Customer Adoption Model

All four examples described in this paper depend on a common DER-CAM optimisation engine, which has been under development at Berkeley Lab for a number of years.

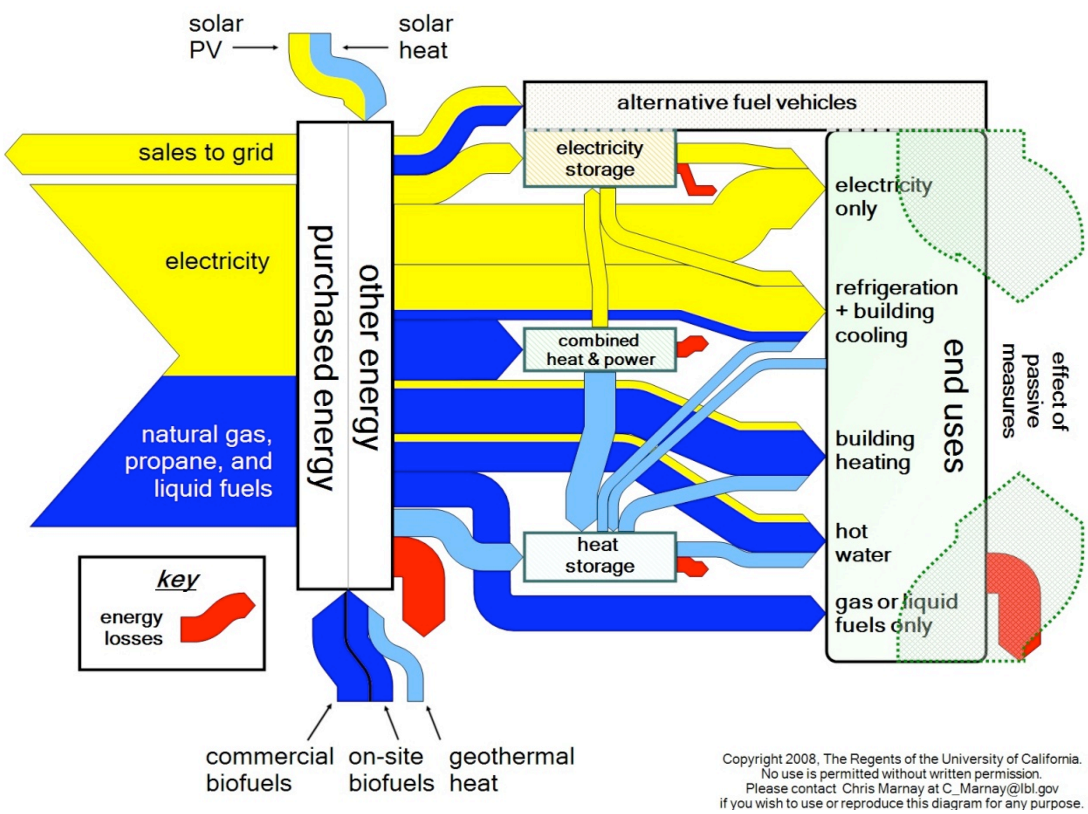

Figure 1 Energy Flows in a Building μ·Grid

DER-CAM solves a μ·grid's investment optimisation problem given its end-use energy loads, energy tariff structures and fuel prices, and an arbitrary list of equipment investment options. The Sankey diagram in Figure 1 shows energy flows in a building-scale μ·grid.

DER-CAM analysis begins with the services requirements shown on the right, which are typically subdivided into electricity only, e.g. lighting, computing, etc. Farther to the right, passive measures are shown, i.e. many services can be provided by improving the building envelope, by daylighting, etc., which tend to lower the requirements on active systems shown to the left.

DER-CAM takes simultaneity of solutions into account. Cooling is the classic example of the simultaneity effect, i.e. partially cooling a building using waste heat fired absorption technology simultaneously lowers the residual peak electrical load and permits bill savings and downsising of all electrical systems, including on-site generating capacity. Identifying the best solution requires correctly trading off these costs and benefits of non-electrical cooling.

Figure 2 shows the data flow and results in DER-CAM, which is implemented as a mixed-integer linear program on the General Algebraic Modeling System (GAMS®) platform using the CPLEX® solver.

The high-level optimization formulation used in DER-CAM follows the standard linear programming approach:

$$\min\ f = c^T \cdot x = \begin{pmatrix} c_1 \\ \dots \\ c_n \end{pmatrix}^T \cdot \begin{pmatrix} x_1 \\ \dots \\ x_n \end{pmatrix} = c_1 \cdot x_1 + \dots + c_n \cdot x_n \qquad (1)$$

s.t.
$Ax \leq b$
$L \leq x \leq U$

where:

c	cost coefficient vector
x	decision variable vector
A	constraint coefficient matrix
b	constraint coefficient vector
L	decision variable lower boundary vector
U	decision variable upper boundary vector

The objective function f, which can be either a cost or CO_2 emission function, will be minimised by varying the decision variables x. DER-CAM also allows multi-objective optimization, with weighted cost and CO_2 functions. The full mathematical formulation with all equations and constraints is roughly 17 pages long and cannot be included here, but can be provided to interested researchers upon request.

This approach is fully technology-neutral and can include energy purchases, on-site conversion, both electrical and thermal on-site renewable harvesting and/or storage, and end-use efficiency investments. Regulatory, engineering, and investment constraints are all considered. Energy costs are calculated using a detailed representation of utility tariff structures and fuel prices as well as amortised DER investment costs and operating and maintenance expenditures.

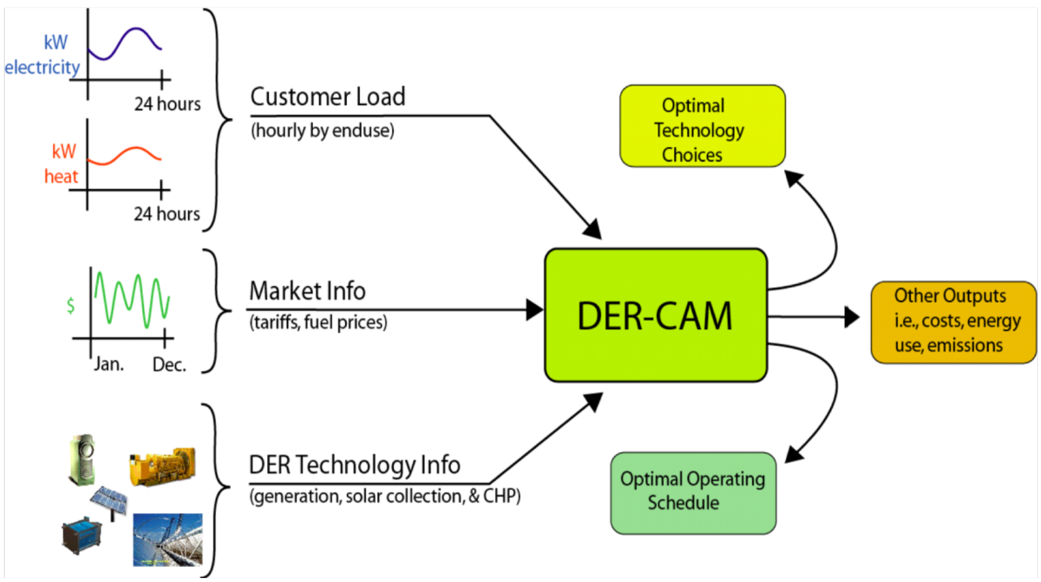

Figure 2 DER-CAM Inputs and Outputs

The source of end-use energy load estimates is often simulated or modelled data, for example, from DOE-2, eQuest, or EnergyPlus. A limitation of simulation data is that a significant change in the building's equipment invalidates any simulation based the prior condition. This work does not take this issue into account. Ongoing development work will permit re-simulation with the recommended equipment fleet and operations, which also enables interactions between end-uses to be considered.

However, monitored data is increasingly available as data acquisition and archiving systems such as OSIsoft's PI Server described below become more widespread. Note that in the SVOW case described below, the user can rely on default electricity load shapes or overwrite with hir own.

As noted, an optimal operating schedule falls from the equipment selection problem, but for more complex scheduling closer to real-time, the more specialised *Operations DER-CAM* is used. This model takes the equipment fleet as fixed, and finds its optimum schedule over user-defined time steps and time horizon, typically 15 min and a week. The common time-step of 15 min reflects the way tariffs are usually defined in California, and a week-ahead schedule is convenient for two reasons. First, seeing both workdays and weekend days makes understanding of the schedules more intuitive. Second, if a daily update fails, the schedules from recent days are suitable substitutes.

APPLICATION 1: SVOW

Project Description

California's non-residential sectors offer many promising applications for electrical storage. The state's time-of-use tariffs, which usually include a stiff demand (monthly peak power use) charge, present an incentive for storage of off-peak electricity for use on the subsequent on-peak period (usually hours 12:00-18:00). Further, the ongoing introduction of Peak Day Pricing (PDP), which imposes extreme prices on about 12 afternoons a year when the grid is stretched, tends to further enhance the load shifting incentive.

Choosing and operating storage under complex tariff regimes poses a technical and economic problem that is likely to discourage potential battery adopters, resulting in foregone economic savings. Vendors offering limited equipment lines are unlikely to provide adequate environmental analysis or unbiased economic results to potential clients, and are even less likely to completely describe the robustness of choices in the face of changing fuel prices and tariffs.

Given these considerations, site managers need a place to start their quest for independent technical and economic guidance on whether storage is even worth the considerable analytic effort. The SVOW open access, web-based, electrical storage and PV analysis calculator has been designed and developed to provide economically sound and technology-neutral guidance. SVOW resides on a Berkeley Lab server, and is powered by an analytic engine consisting of a simplified DER-CAM model that considers only electricity use and focuses on just the technologies of interest. Nonetheless, storage optimisation under complex tariffs is an analytic challenge and SVOW provides a powerful tool for large electricity customers.

Status

SVOW aims to provide basic guidance on whether available storage technologies, PV or combinations of these technologies merit deeper analysis. The battery alternatives include both standard and flow batteries. The latter are more complex to optimise because multiple energy-power combinations are possible. Since the non-residential sectors encompass a broad range of facilities with fundamentally different characteristics, the tool first asks the user to select a load profile from a limited cohort group of example facilities. These examples may be modified by the user to better fit a site's unique circumstances. After the load profile selection, the user will be prompted to select a tariff, the cost option, and so on, until all of the parameters are specified.

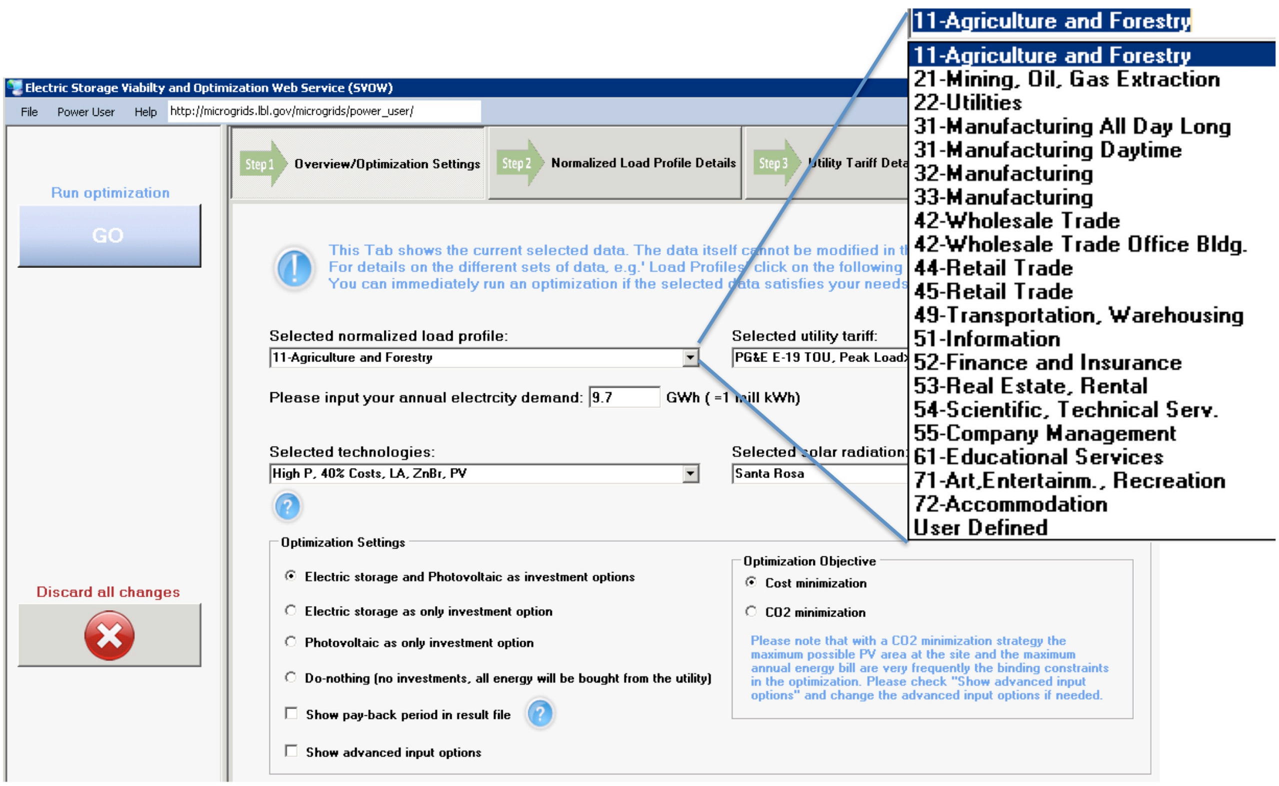

Figure 4 SVOW Start Up Page

Figure 4 shows the start-up page where the user sees an overview of options and settings, including 20 available default load profiles that can be selected from a pull-down menu. Representative tariffs are available for large customers in Sempra Utilities (San Diego area), Southern California Edison, and Pacific Gas and Electric (PG&E, northern California).

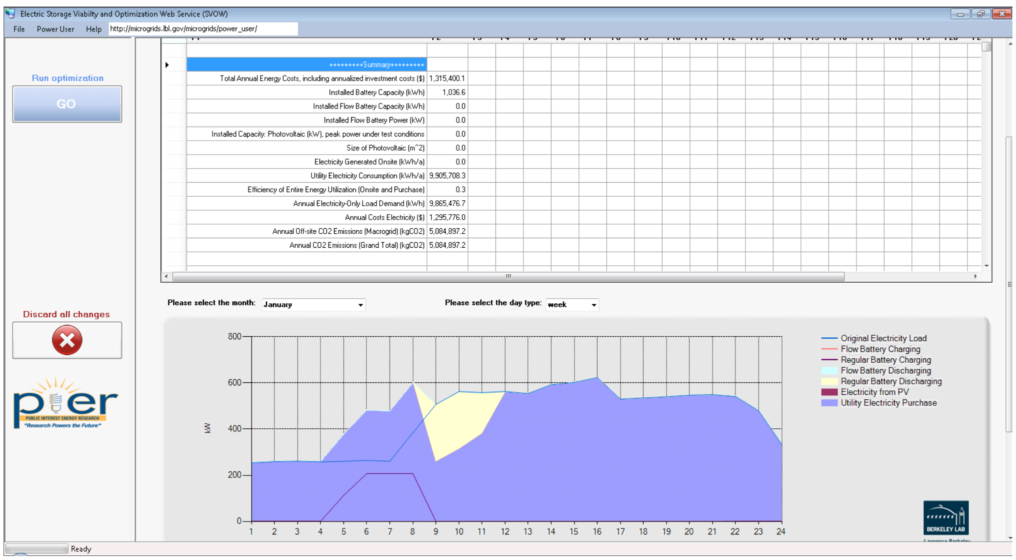

Figure 5 SVOW Results Page

A typical results page is shown in Figure 5. In this example, batteries are selected but without any PV. The user is shown estimated annual bill savings and details on selected technology. A result of particular note is an estimate of the effect of adoption on the site's greenhouse gas footprint. Hourly marginal emissions estimates are based on the Greenhouse Gas Calculator (GHG) from the consultancy Energy and Environmental Economics (E3) **[8]**. E3 derived the emissions by simulating the generation capacity and mix within the Western Electricity Coordinating Council, and the emissions represent the CO_2 contribution from energy consumed in California regardless of whether the energy was generated in-state or out-of-state **[8]**. Graphics also show operations on typical days. The example shows battery charging during the night-time and morning, with discharging during the late morning k period, which would be a typical winter schedule. During the winter, there is no high afternoon energy or power charge, so there is no advantage to saving energy for the late afternoon. Additionally, stand-by charge losses encourage last minute charging, and absent other incentives, immediate discharge.

Results

SVOW has been available since mid-2010. Approximately one hundred users had established accounts by the end of January 2011.

APPLICATION 2: UNIVERSITY OF CALIFORNIA, DAVIS (UCD)

Project Description

Together with OSIsoft LLC as its private sector partner and matching sponsor, the Berkeley Lab won a U.S. Department of Energy (U.S.DOE) grant to further the commercialisation of DER-CAM using a web-based software as a service (SaaS) model.

A pilot demonstration was conducted at the Segundo Dining Commons building (4650 m^2) on the UCD campus. The Commons is the dining hall for students living in nearby dormitories, and also the main central kitchen providing food to other campus buildings.

Berkeley Lab accessed the historical and real-time electricity, natural gas, steam, and chilled water usage information for Segundo using OSIsoft's PI to PI protocol. Historical daily high/low and hourly high/low 7-day ahead forecast temperatures are stored in Berkeley Lab's time-series database and used as input to a week-ahead demand forecaster regression model. The temperature forecast is automatically updated every day from the National Oceanic and Atomospheric Administration website. Marginal GHG emissions are taken from the E3 model.

The campus currently buys electricity through the Western Area Power Administration at an essentially flat and very favourable tariff of $0.085/kWh. Berkeley Lab set out to investigate a hypothetical scenario wherein UCD has to purchase electricity on a PG&E standard tariff, and to derive an optimal carbon minimising schedule for the building.

Status

Daily forecasting and scheduling has been implemented. Whenever a user executes the SaaS model , a user-friendly, web-based interface to DER-CAM, s/he does it through a secure Remote Desktop Connection (Terminal Services Client 6.0) and does not need to have any specialised software installed or run any other program. The SaaS model collects data from Berkeley Lab's PI server using

DataLink, a standard OSIsoft product, and also calls the format changer macro, which converts the raw PI data to a DER-CAM usable form. The SaaS model can execute both the investment planning and the week-ahead *Operations DER-CAM*.

Since OSIsoft's PI system does not currently support data feed-back, the optimisation results cannot be sent back to the building directly. The week-ahead optimisation capabilities have been developed in principle, but are not implemented in the SaaS model because no practical method is available to automatically implement schedules at Segundo.

Results

While not fully complete and operational, the Web Optimization arrangement successfully demonstrated the viability of providing building µ·grid optimisation using a SaaS model. The UNM project described below represents an actual live implementation of this approach.

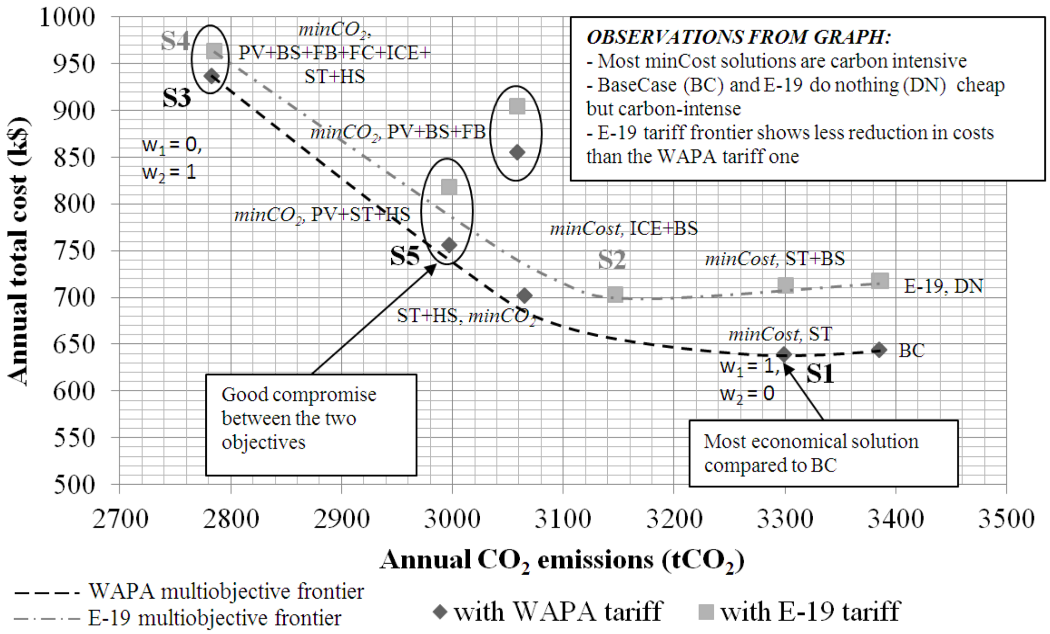

Figure 6 Cost-CO_2 Trade-Off Frontier

Figure 6 shows an example for Segundo of one of the more interesting outputs of a DER-CAM multi-objective optimisation, the cost-CO_2 trade-off curve. The current combination of carbon emissions and costs appears at the bottom right (w_1=1,w_2=0). Increasing the weight of carbon (w_2) in the objective function produces results further to the left, i.e. with higher costs but lower carbon footprint. As mentioned above, this result was of particular interest to UCD, which is keen to have an impact on climate threats.

Being a large cooking facility, the Commons has a significant heat load normally met by a campus heat loop. In this optimisation, other options to this arrangement are sought. Note that DER-CAM can jointly optimise the electricity and heat supply to a μ·grid, making it particularly powerful for selecting CHP systems, or combined waste heat recovery ST systems.

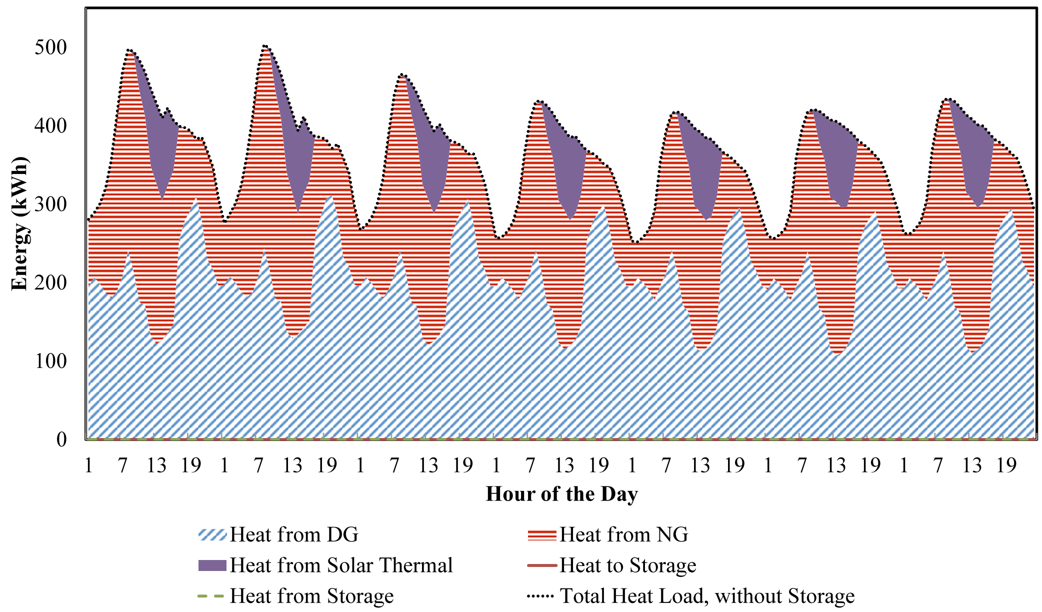

Figure 7 Heat Balance for a January Week

Figure 7 shows the heat balance from a particularly complex Commons case, in which both reciprocating engine and fuel cell CHP was selected, and the system also includes ST collectors. CHP provides significant heat in all hours, while the ST system augments it during the afternoons. Natural gas is used make up the shortfall. Note that with only inputs describing the technologies and hourly service requirements, DER-CAM is finding both the optimal equipment configuration and this complex operating schedule for it.

APPLICATION 3: SANTA RITA JAIL

Project Description

The Alameda County correctional facility, the Santa Rita Jail, opened in 1989. It currently holds ~4,500 inmates on a 9 ha property and is considered one of the most energy efficient prisons in the U.S. The County has a long history of using innovative approaches to increase energy efficiency and reduce public costs. The Jail has a fairly flat load with an electricity peak demand of about 3.0 MW, and County naturally wants to further save on its utility bills.

A 1.2 MW PV system covers most of the cellblocks. When installed in spring 2002, it was the biggest in the U.S. In May 2006, the County added a 1 MW molten carbonate fuel cell with heat recovery providing hot water pre-heating for domestic hot water requirements.

For various reasons, the County decided to install a large (2 MW and 4 MWh) Li-ion battery at the Jail. The project is partially funded by U.S.DOE under its Smart Grids program. The battery is equipped with Consortium for Electric Reliability Technology Solutions (CERTS) Microgrid capability, which allows the Jail to disconnect from the grid and run islanded for extended periods **[9]**. A static switch at the Jail's substation will permit rapid disconnect and reconnect. Note that in this µ·grid, the battery represents the only controllable resource, so it must maintain energy balance alone.

Under the terms of the U.S.DOE grant, the Jail must contract with PG&E to reduce the peak load on the local feeder by 15%. Reliability is also a major concern, particularly having enough energy to maintain full service during the break between a blackout beginning and the back-up diesel generators reaching full power, typically a few minutes.

Berkeley Lab used DER-CAM to assist with the selection of a battery vendor. Now the battery is installed, DER-CAM will be used to find optimal charge-discharge schedules minimising its bill and meeting its other objectives. Note that the optimisation is very complex in this case because of the multiple objectives and the introduction of uncertainty in some variables, e.g. neighbouring feeder loads and outages. Outages of the fuel cell have a particularly dramatic negative affect on bills. An uncertainty based version of DER-CAM has been developed for just such applications.

Status

Figure 8 shows the hourly energy balance of the Jail in 2008. The blue series is the PV energy. This is a good solar site so PV output is fairly reliable. The red line shows fuel cell output, and the purple series is the total electricity use. Purchases from PG&E under a standard tariff are shown in green. In general, neither has the PV system performed well and nor has the fuel cell been reliable. Grid purchases have therefore far exceeded expected levels, with serious cost consequences for the County. Note that a high average power draw of only 15 min triggers the punishing demand charge.

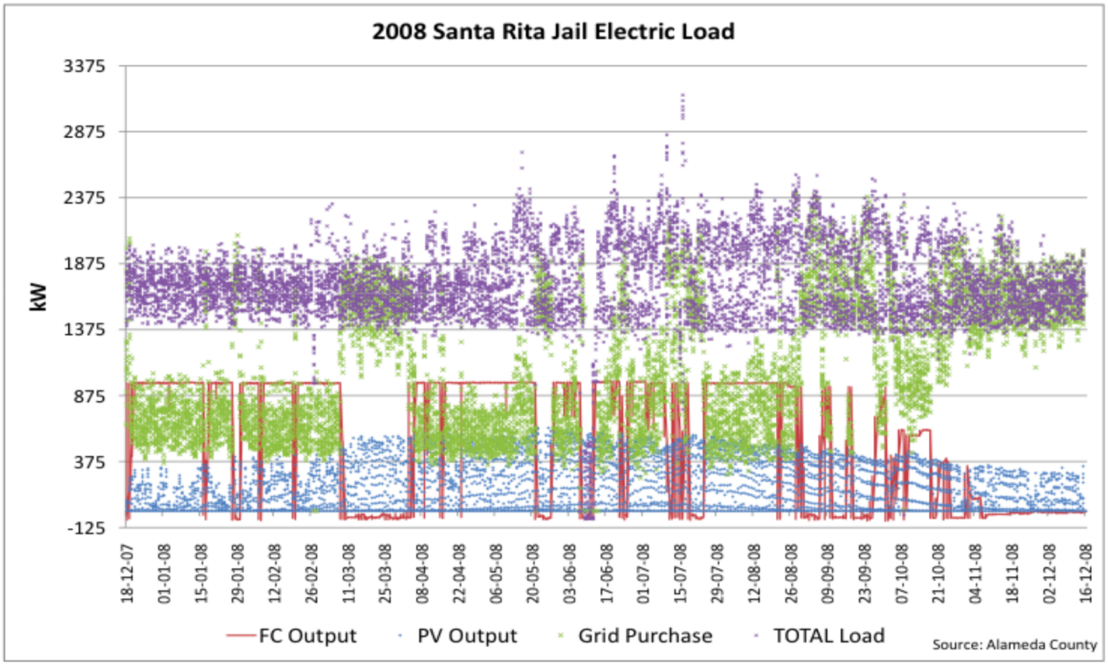

Figure 8 Jail Electricity Balance

Table 1 shows the effective tariff at the Jail. Note the cost and complexity of the demand charge, which has three components: 1. a charge of \$12.67/kW for the on-peak maximum power, 2. a charge of \$2.81/kW for partial peak maximum power, and 3. a further \$8.56/kW charge for maximum power at the time of the site's own peak, irrespective of timing. The upshot of these charges is that in the summer months, peak charges account for a third of the Jail's bill. Finally, together with most large customers in California, the Jail will soon be exposed to PDP. This means that between 9 and 15, with an average of 12, afternoons per year and with a day's warning, PG&E will levy an extra \$1.20

per kWh, while base rates will lower slightly. This structure will make the summer on-peak price roughly \$0.14/kWh normally, but the peak days will effectively raise the average to \$0.24/kWh.

Table 1 ***Effective Jail Tariff***

E-20 Rate Summer Tariff Parameters	**Value**
Peak Hours	12:00 - 18:00
Partial Peak Hours	8:30 - 12:0018:00 - 21:30
Off Peak Hours	21:30 - 8:30
Peak Energy (\$/kWh)	0.14606
Partial Peak Energy (\$/kWh)	0.10168
Off Peak Energy (\$/kWh)	0.08339
Max Peak Demand (\$/kW)	12.67
Max Part Peak Demand (\$/kW)	2.81
Monthly Max Demand (\$/kW)	8.56

Results

A version of DER-CAM similar to the SVOW engine was used to evaluate 6 battery vendor proposals for the installation using 5 chemistries. Figure 10 shows what the 7-day rolling charging schedule might look like for an October week. These results come from a week-ahead optimisation using Operations DER-CAM, a version of the tool that generates optimal operations schedules for fixed capacities of DER equipment over user-defined timesteps and horizon. Note this example shows a 2 MW and 12 MWh sodium-sulphur (NaS) battery, which is not the one ultimately installed, but which produced particularly interesting results.

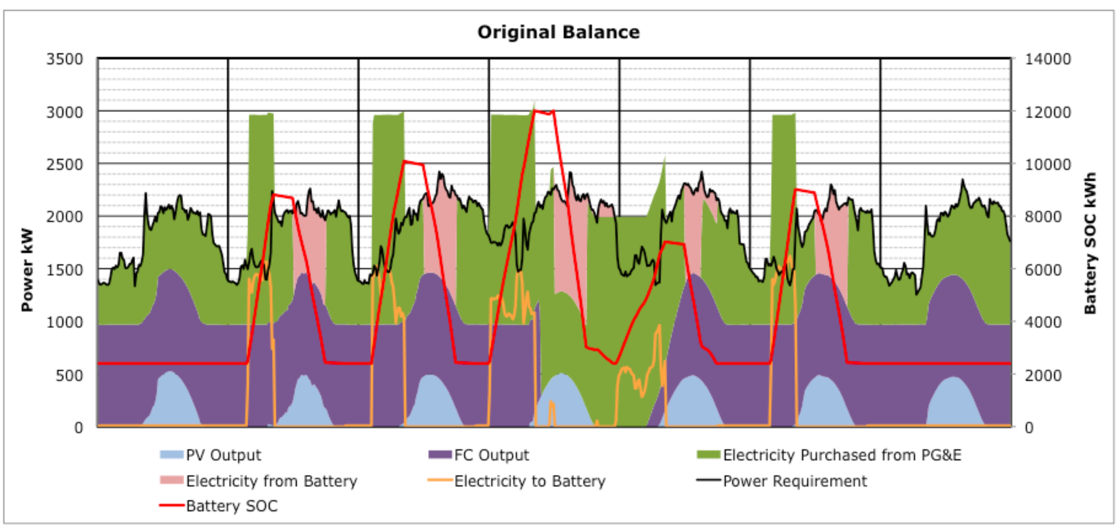

Figure 10 Example Charging Schedule

The black line is the Jail's total load. As is quite apparent, loads are fairly easily forecast. The PV output is shown at the bottom in blue, and the fuel cell output above it in purple. Note there was a fuel cell outage during this week. The green area is energy purchased from PG&E. When the green exceeds the total load the battery is being charged. The red line shows the state of charge of the battery.

The state of charge is generally determined by the expected requirements of the following day, shown by the pink discharged energy. Note that the battery is left discharged on the two weekend days, which are the first and last days shown in the graphic. The round-trip efficiency of NaS batteries is fairly low, and about 70% is assumed in this optimisation, so there is a high cost to storing and retrieving energy that limits use of the battery to times when its benefits are significant. Surprisingly, the battery is not charged as much during the fuel cell outage as on neighbouring days. Note that on Thursday afternoon the pink discharge is smaller, incurring significant on-peak charges, which is a counter intuitive result. Detailed analysis of this example revealed that this schedule is indeed optimal. The reason for the low charge on Thursday is that the partial peak demand charge bill increase would be costlier than the on-peak burden of the low state of charge. The orange line is the optimal charging instruction to the Jail for its battery operation.

As noted above, a central objective of the Santa Rita Jail project is to achieve a coordinated lowering of the peak load on the local utility feeder. DER-CAM results for the hottest summer week in 2009 shows that the NaS battery alone could reduce feeder peak by about 9%, unfortunately short of the 15% goal. On the positive side, if peak reduction credit is additionally taken for all the efficiency measures as well as the PV and fuel cell generation installed over the past 10 years, then the now controlled Jail µ·grid can reduce the approximately 14 MW feeder peak by about 20%. Interestingly, the net cost to the Jail of operating away from its bill minimising schedule for this purpose only raises its utility costs by about $400, inconsequential in its annual approximately million dollar costs.

APPLICATION 4: UNIVERSITY OF NEW MEXICO (UNM)

Project Description

In collaboration with UNM, Operations DER-CAM is being used to optimise cooling equipment scheduling at the campus Mechanical Engineering building **[10]**. Present at this building is a diverse array of thermal equipment, including solar thermal water heating (~230 m^2), hot (~ 300 kWh or 30 m^3) and chilled water storage (~3800 kWh or 300 m^3), and a small single effect absorption chiller. Given the hot, arid local climate, cooling represents the dominant end-use (about 300 kW thermal peak demand), and thus there is potential for significant cost savings from DER-CAM optimisation.

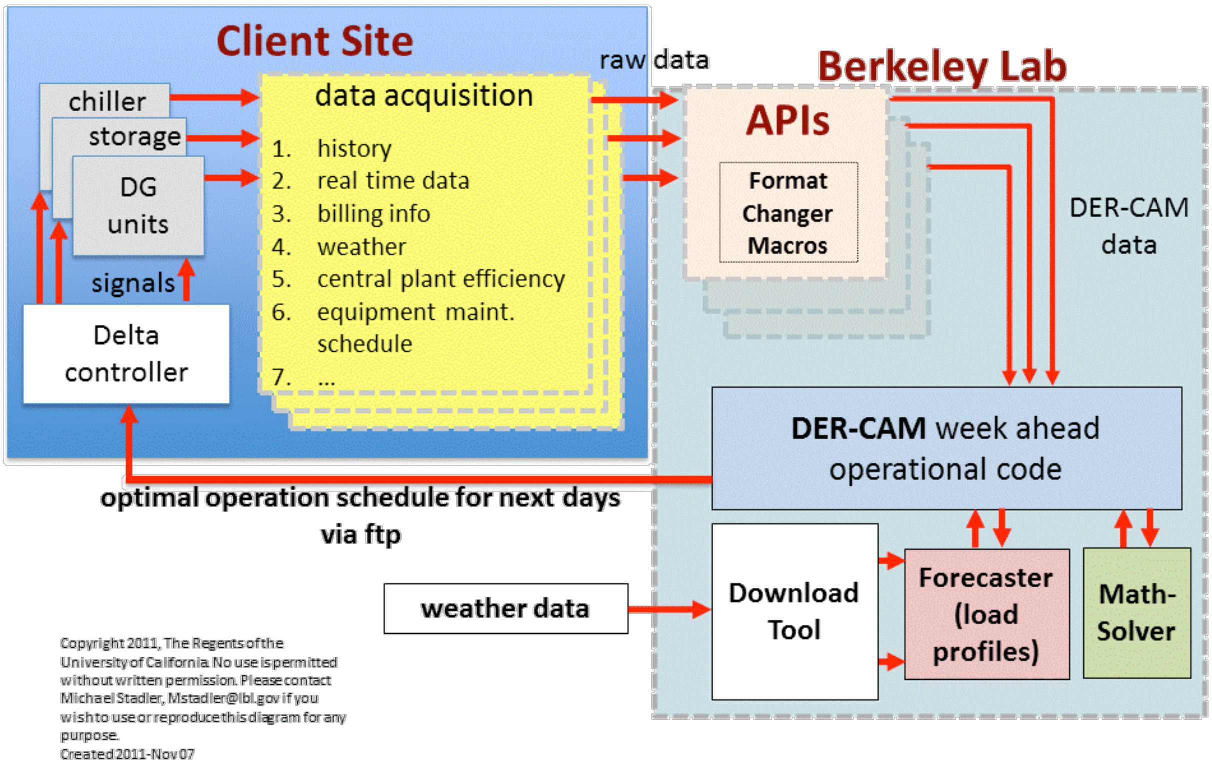

Figure 12 Data flow for University of New Mexico Project

The objective of this project is to establish an automated process to forecast building end-use demand and resources (e.g. insolation), create optimised dispatch schedules for the various thermal equipment and communicate the results back to the building control system for execution. Figure 12 shows the data flow for this project, and exemplifies how a daily operations optimisation would be implemented. Data are received via application programming interfaces (APIs) from the building. These together with input data from elsewhere provide a week-ahead load and solar output forecast, which is fed into Operations DER-CAM to find an optimal schedule. This schedule is returned to the building using a simple ftp transfer and is fed directly into the building's EMCS. In this case, operation of an absorption chiller and charging-discharging of heat and coolth storage are being optimised.

Status

At present, DER-CAM has been successfully deployed to deliver week-ahead scheduling of energy flow to and from storage as well as absorption chiller start/stop times to the UNM building controller in an automated fashion. Several developments to Operations DER-CAM were necessary before meaningful schedules could be generated. Integration of cold storage was the first requirement, and simply followed the structure of other storage technology types present in DER-CAM. The second task required that the technology constraints in the code, particularly those on the absorption chiller, were an accurate reflection of the real world operational constraints. These constraints were implemented such that the linearity of the model was maintained. Finally, a regression based forecaster was constructed for the Albuquerque area to forecast cooling loads based on important driving factors including temperature and time of day.

Results

With the expanded DER-CAM functionality, week-ahead operations schedules, as seen in Figure 13, are generated daily. The figure shows operation of the UNM thermal system for a generic hot, clear week beginning Monday. The cold storage state-of-charge is also shown on the right axis. The absorption chiller is constrained to binary on/off operation and is limited to 2 cycles per day, in accordance with real-world limitations. Cold storage is also deployed, and is sufficient to meet all on-peak cooling demand. As a result, heat collected from the solar thermal system can be stored and used during off-peak hours to partially recharge cold storage. This behavior occurs both because of the higher efficiency of nighttime cooling in this high desert climate, and because of a 4 kW pumping cost associated with running the absorption chiller. Although the cooling requirement is similar, note also that storage is not used on the weekend, when the tariff differential does not justify it. This year, 2012, offers the first summer of data collection on this system and results comparing the prior operating schedules and DER-CAM optimized ones are expected by the end of the year.

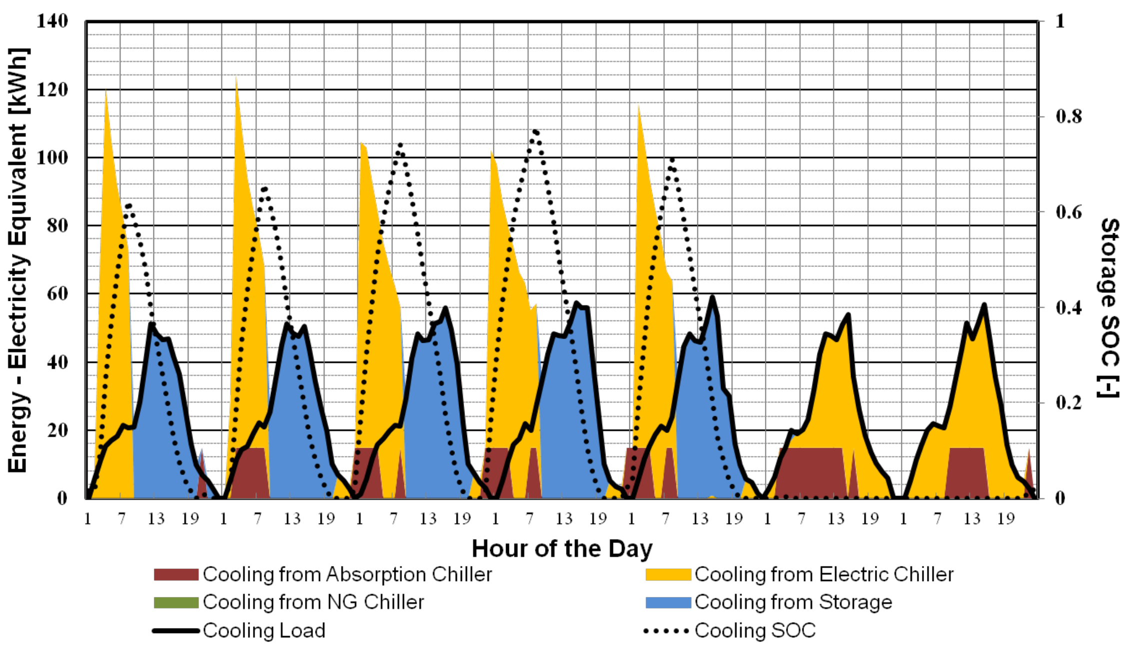

Figure 13 Week-ahead DER-CAM Optimisation of Cooling

CONCLUSION

Multi-technology building μ·grid design and operation under highly variable conditions poses a significant challenge that must be overcome to drive down carbon emissions at reasonable cost. A systemic optimisation is necessary to achieve the overall best results, i.e. one in which as many available options as possible compete and collaborate.

Berkeley Lab is developing optimisation methods for solving these problems. Considerable detail is required to adequately characterize the energy services requirements of a facility. Building energy simulation is often used to provide input data. The basis of DER-CAM methods has been described and four applications presented. A web-based SaaS model is being pursued to free building designers and operators from the burden of hefty optimisation problems. This overall approach has been highlighted by four examples. All four are ongoing projects and will still yield considerable additional results. In the examples shown, relatively little demand-side technology is represented, and in general representing efficiency measures is more difficult than supply technologies. Additionally, if simulation data inputs are used, they may become invalidated if building characteristics are significantly altered.

Interested readers can try out a simplified version of DER-CAM called WebOpt at http://der.lbl.gov/der-cam/how-access-der-cam/.

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GLOSSARY

μ·grid: a true microgrid that is within one site and usually behind one meter that is able to island from the surrounding grid

CEC: California Energy Commission

CERTS: Consortium for Electric Reliability Technology Solutions

CHP: combined heat and power

CIGRÉ: Conseil International des Grandes Réseaux Electriques

DER-CAM: Distributed Energy Resources Customer Adoption Model

EMCS: energy management and control system

ftp: file transfer protocol

GAMS: General Algebraic Modeling System

HVAC: heating, ventilation, and air conditioning

LBNL: Ernest Orlando Lawrence Berkeley National Laboratory

NaS: sodium sulphur battery

PDP: Peak Day Pricing

PV: solar photovoltaic systems

SaaS: Software as a Service

ST: solar thermal

SVOW: Storage Viability Web Service

UCD: University of California, Davis campus, near Sacramento

UNM: University of New Mexico, Albuquerque campus

U.S.DOE: the U.S. Department of Energy